A Comparative Study of NMPC Strategies for Prioritized Multi-UAV Trajectory Tracking with Collision Avoidance in Agricultural Field Mapping Missions

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***Abstract*—In agricultural field mapping missions, a collision risk occurs when the UAVs deviate from their planned trajectories due to the wind or uncertainties in the model, but also in case of intersecting paths of the UAVs, e.g. when the battery level is not sufficient and a UAV needs to change its initially planned path and return to the base unexpectedly.**

In this paper, three nonlinear model predictive control (NMPC) trajectory tracking strategies for collision avoidance are compared for multi-UAV mapping of an agricultural field: incorporating collision avoidance as a nonlinear constraint, applying it as a penalty cost, and employing a safe flight corridor approach. All the presented strategies consider passing priority allocation of the UAVs involved in the mission, where only a UAV with a lower-level priority handles collision avoidance.

Control strategies are compared regarding robustness to external disturbances, such as wind, and model uncertainties through Monte Carlo simulations. The performance is evaluated with respect to the resulting tracking errors, the ability to avoid collision, and the computational time needed to solve the optimal control problem. The objective is to determine, among these three approaches, the one that exhibits the best trade-off between performance and computational burden.

***Index Terms*—trajectory tracking, multi-UAV system, collision avoidance, predictive control, prioritized planning**

I. INTRODUCTION

UAVs have seen a growing potential in application in various smart agriculture tasks [1]. One of those tasks includes mapping of an agricultural field [2]. UAVs are replacing conservative methods to improve efficiency and accuracy. As such, multi-UAV systems are often employed to map the field to reduce the mapping duration and thus ensure increased mission efficiency, especially for large fields. In this case, coordination between the UAVs engaged in the same mission must be considered to ensure safety, namely to avoid collision.

A suitable control strategy needs to be developed to find a safe optimal trajectory with minimal tracking error while avoiding collision between the UAVs. Nonlinear model predictive control (NMPC) has proven a higher level of robustness than linearized MPC, while implemented in real-time systems [3]. A distributed approach to MPC has been extensively researched and used in applications such as field mapping. In distributed MPC [4], each UAV computes its own optimal control inputs with respect to the predicted behavior of the system based on the model, as well as the predicted behavior of neighboring UAVs, while respecting constraints. Thus, it provides better scalability and tractability compared to centralized coordination [5].

Different approaches to collision avoidance in multi-UAV systems have been proposed in the literature. In [6]–[8], collision avoidance is imposed as a nonlinear constraint while computing the optimal trajectory for each UAV. In [9], collision avoidance is handled in the cost function, and its significance can be adjusted depending on the need for collision avoidance. Inspired by the multi-objective MPC [10], a state-dependent cost function criterion to avoid collision when necessary is presented in our previous work [11]. Staying within a defined safe flight corridor is another approach to avoid collision and smoothen the trajectory. In [12], feasible flight corridor is constructed based on a graph of interconnections in the multi-obstacle environment. Flight corridors in [13] are defined by a radius around the sphere waypoint, which allows the UAV to perform more natural turns while remaining inside the imposed corridor.

In order to enhance the multi-UAV mission performance and safety, attributing different levels of passing priority to the UAVs involved in the same mission can aid in resolving a collision conflict. Prioritized planning has been explored for resolving motion planning coordination in multi-robot systems. The collision resolver introduced by [14] is triggered when the path of one robot is blocking another robot's path. Based on their predetermined priority level, lower-priority robot needs to wait or diverge from the initial route in order to let the higher-priority vehicle pass by respecting the spatio-temporal constraints. This is done by introducing a collision resolver which is triggered when a higher-priority robot blocks a lower-priority one's path. The collision resolver tries to find a path that avoids the other robot's route, taking spatial and temporal constraints into account. Multi-UAV path planning and trajectory tracking with passing priority is discussed in [15]–[17]. In our previous work [18], we emphasize the importance of prioritized trajectory tracking to eliminate unnecessary maneuvers, resulting in increased mission safety, as well as lowering total energy consumption. Prioritized collision avoidance cost function to avoid other UAVs, as well as other obstacles, is also presented in [19].

In this paper, we present a comparative analysis of three nonlinear MPC strategies to avoid collision with predefined passing priority applied to the trajectory tracking for agricultural field mapping, in order to choose the most adequate one to implement on the considered real-life application. All the proposed strategies are consensus-based extensions of distributed MPC, with information exchange between the UAVs. Standard collision avoidance strategies, as a nonlinear constraint and cost function criterion, are compared to the proposed safe flight corridor approach. Control strategies are assessed in terms of robustness to model uncertainties and external disturbances, as well as the computational complexity being an important parameter when considering a real-time application. Robust strategy must perform with the low tracking error and successfully avoid the collision if a risk appears. In a field mapping mission,

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collision risk can arise when the UAV deviates from its initially planned path due to the wind or uncertainties in the system model, as well as in case of insufficient energy to finish the mission when the replanned paths of the UAVs intersect.

The rest of the paper is organized as follows. Section II introduces the nonlinear model of the UAV used in simulations. Section III describes the multi-UAV mission considered as a case study. Different collision avoidance distributed NMPC strategies are presented in Section IV, while simulation results are summarized and discussed in Section V. Finally, concluding remarks are provided in Section VI.

II. UAV DYNAMIC MODEL

The nonlinear representation of a quadrotor with 6 DOF is modeled by the following set of nonlinear equations [7]:

$$\dot{p}(t) = v(t), \tag{1}$$

$$\dot{v}(t) = R \begin{bmatrix} 0 \\ 0 \\ \alpha T \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ -g \end{bmatrix} - \begin{bmatrix} A_x & 0 & 0 \\ 0 & A_y & 0 \\ 0 & 0 & A_z \end{bmatrix} v(t) + \begin{bmatrix} w_x \\ w_y \\ w_z \end{bmatrix}, \tag{2}$$

$$\dot{\phi}(t) = (K_\phi \phi_{ref}(t) - \phi(t))/\tau_\phi, \tag{3}$$

$$\dot{\theta}(t) = (K_\theta \theta_{ref}(t) - \theta(t))/\tau_\theta, \tag{4}$$

The vector $p = [p_x, p_y, p_z]^\top$ defines the position, while the vector $v = [v_x, v_y, v_z]^\top$ denotes the velocity. These vectors result from the transformation to the yaw-compensated global reference performed with the rotation matrix $R \in SO(3)$, which represents the orientation of the body-fixed reference frame with respect to the global reference frame. The attitude of the UAV is also given in the global coordinate system and characterized by roll, ϕ, and pitch angle, θ. In the equations, the yaw angle, ψ, is set to zero and regulated by an inner P-controller as in [7]. In (2), the external disturbances, such as wind acting on a UAV as torque, are represented by the addition of the vector $w = [w_x, w_y, w_z]^\top$. The parameter α signifies the thruster efficiency, which is equal to 1 in the nominal case. Other parameters represent gravity, g, linear dumping terms, A_x, A_y, A_z, time constants, τ_ϕ, τ_θ, and gains of the inner-loop actions for the attitude control, K_ϕ, K_θ. Their values are fixed as in [7]. Control inputs include total thrust, reference pitch and roll angles, denoted as $u = [T, \phi_{ref}, \theta_{ref}]^\top$. System dynamics is therefore described by 8 state variables $\mathbf{x} = [p, v, \phi, \theta]^\top$, 6 outputs $\mathbf{y} = [p, v]^\top$ and 3 control inputs $u = [T, \phi_{ref}, \theta_{ref}]^\top$.

The discretized model is issued from the continuous model (1)-(4), discretized at the sampling time T_e, using the Runge-Kutta scheme, with f as a nonlinear function:

$$x_{k+1} = f(x_k, u_k, w_k), \quad k \geq 0, \tag{5}$$

where k represents the time step. The control inputs and disturbances are constant between the two time instants in further study.

III. MULTI-UAV MAPPING MISSION

The mapping mission of an agricultural field with the UAVs includes two phases: path planning and trajectory tracking. Path planning results in determining the waypoints where a UAV needs to take a snapshot to cover the entire field. In this phase, parameters such as camera characteristics, battery, etc., need to be considered when planning the optimal path.

Time-efficient mapping of an agricultural field often involves multiple cooperative UAVs. To ensure safety when employing a multi-UAV system in this type of mission, avoiding collision along the trajectory is necessary.

Based on the path plan for mapping the vineyard and olive orchard in [20], a simplified layout of the reference paths of two UAVs in the studied mission is given in Figure 1 and the coordinates of the waypoints in Table I.

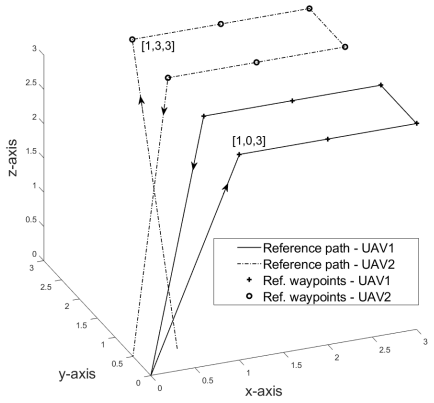

Fig. 1. Reference path for the mapping mission with two UAVs.

TABLE I
REFERENCE WAYPOINTS

Waypoint	UAV1	UAV2
$start$	$(0,0,0)m$	$(0.5,0.5,0)m$
1	$(1,0,3)m$	$(1,3,3)m$
2	$(2,0,3)m$	$(2,3,3)m$
3	$(3,0,3)m$	$(3,3,3)m$
4	$(3,1,3)m$	$(3,2,3)m$
5	$(2,1,3)m$	$(2,2,3)m$
6	$(1,1,3)m$	$(1,2,3)m$
$finish$	$(0,0,0)m$	$(0,0.5,0)m$

As this is a homogeneous multi-UAV mission, both UAVs have the same camera parameters and therefore, fly at identical and constant reference altitude. Even though the planned paths do not intersect and the distance between agents' waypoints is at least 1 m at all times, a risk of possible collision needs to be considered as it is present at take-off and landing from and to the points in close proximity, or in case of deviation from the planned path. Deviation can be caused by numerous reasons, such as external disturbances, model uncertainties, emergency landing due to fault in the system, etc.

To avoid unnecessary maneuvers and path alternations, only one of the two UAVs will handle collision avoidance. Hierarchical passing priority is allocated to a pair of the UAVs, such that the UAV with higher passing priority focuses only on the trajectory tracking in its control strategy, whereas the UAV with lower passing priority needs to avoid collision in addition to the trajectory tracking. Resulting in smoothened trajectories of both UAVs, fewer alternations account for augmented safety and less energy consumed during the flight. At the planning level, higher priority should be given to the UAV with a lower battery level, smaller overall path distance, or based on another determined criterion. In this study (Figure 1), priority is given to UAV2, while UAV1 is responsible for collision avoidance when the risk appears along the trajectory.

Control is handled in a distributed manner, with output information exchanged between the UAVs as described on the schematic diagram in Figure 2. As shown in the figure, UAV1 takes both its own predicted output and the predicted output of the UAV2 as input for the chosen optimal control problem defined later in this paper. Model uncertainties and

external disturbances are also considered when describing the real system.

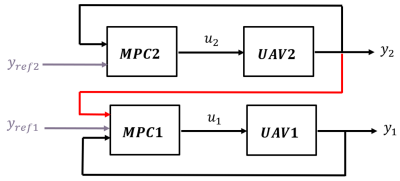

Fig. 2. Distributed MPC schematic diagram.

The distributed approach implies that each UAV computes its own control inputs based on the predicted outputs $\hat{\mathbf{y}}$ over a certain prediction horizon of length $N_p \cdot T_e$. Predicted outputs are acquired based on the model (5).

The objective of the control law is to track the reference output $\mathbf{y}_{ref}$ with precision. Robustness against bounded disturbances and model uncertainties is ensured by considering the error between the model output $\mathbf{y}^{model}$ and the real system output $\mathbf{y}$. To account for the error, the predicted output, at time $(k+n)T_e$ and along the prediction horizon N_p starting from time kT_e, is chosen as:

$$\hat{\mathbf{y}}_{k+n} = \mathbf{y}^{model}_{k+n} + n(\mathbf{y}_k - \mathbf{y}^{model}_k), \quad n \in [1, N_p] \tag{6}$$

The model output $\mathbf{y}^{model}$ is provided by a nominal model, without uncertainties, $\alpha = 1$, nor external disturbances, $w = 0$.

It is assumed that the real system's output is error- and noise-free, and all the state variables are measured. It is assumed that the distrubances w acting on the system are unknown and unmeasured.

IV. Distributed NMPC for Collision Avoidance

Model predictive control (MPC) is a control strategy that repeatedly solves a finite-horizon optimization problem while respecting a set of constraints on states and inputs. Optimization results in control inputs that are chosen to minimize a predicted cost. Future behavior is predicted based on the system model. Nonlinear model predictive control (NMPC) is used when the model is nonlinear, as it is the case with the UAV model (5).

Distributed model predictive control (DMPC) aims to lower the computational complexity of the centralized optimal control problem by dividing it into subproblems for each subsystem, here UAV. Subsystems are coupled through dynamics [21], constraints [22], or cost functions [23].

In DMPC, each UAV in the system is an agent in set $\mathcal{N}_i$, and implements its own control strategy to track the reference output. Additionally, collision avoidance needs to be considered in case of risk of multiple agents being in close proximity. The risk of collision especially arises when the UAVs start and end the mission from the same or similar waypoint. Therefore, to ensure safe take-off and landing, as well as flight of all the UAVs, additional measures need to be included while defining a control strategy suitable for the mission.

Collision avoidance can be addressed in several ways. This study aims to compare collision avoidance handling as a nonlinear constraint, an additional criterion in the cost function and a safe flight corridor.

All the listed strategies for collision avoidance will be applied only to the UAV with the lower-passing priority, whereas classical NMPC will be applied to the higher-passing priority UAV. Cost function of the classical NMPC minimizes the tracking error and change in control inputs:

$$J_i(u^i_{k,\dots,k+N_p-1}) = \sum_{n=1}^{N_p} \left[\|\hat{\mathbf{y}}^i_{k+n} - \mathbf{y}^{i,ref}_{k+n}\|^2_{Q_i} + \|\Delta u^i_{k+n-1}\|^2_{R_i} \right], \tag{7}$$

where Q_i and R_i are weight matrices, and $y^{i,ref}$ the reference for UAV i. The first term considers trajectory tracking, while the second term aims to smooth the variation in control inputs.

A. Collision avoidance as a nonlinear constraint

A nonlinear constraint that prevents collision between the UAVs is imposed as a minimum distance that needs to be satisfied between the positions of the UAVs along their trajectories. Besides the classic NMPC (7), a nonlinear constraint for collision avoidance needs to be satisfied, where the distance between the UAVs i and j, d_{ij}, is kept greater than the defined safety distance d_s over the prediction horizon. Thus, at each sampling time $(k+n)T_e$, following constraint is considered, similarly to [6]:

$$\|d_{ij,k+n}\|_2 \geq d_s, \quad i,j \in \mathcal{N}_i, \quad j \neq i \tag{8}$$

B. Collision avoidance in the cost function

Relaxing the collision avoidance constraint can be transformed into a penalty cost. Thus, the newly formulated cost function includes a new criterion whose weight depends on the proximity from the UAV that needs to be avoided. It is expressed as in [18]:

$$J_i(u^i_{k,\dots,k+N_p-1}) = \sum_{n=1}^{N_p} \Bigg[\|\hat{\mathbf{y}}^i_{k+n} - \mathbf{y}^{i,ref}_{k+n}\|^2_{Q_i} + \|\Delta u^i_{k+n-1}\|^2_{R_i} - \sum_{j \in \mathcal{N}_i, j \neq i} A_{ij}(d_{ij,k+n}) \|d_{ij,k+n}\|^2_{G_{ij}} \Bigg] \tag{9}$$

In (9), in addition to minimizing the tracking error and successive change in control inputs as in (7), the last term in the cost function aims to maximize the distance between the UAVs with the weight factor G_{ij}. Depending on the distance d_{ij} and tuning factor γ, weight A_{ij} can take values in the interval $[0, 1]$:

$$A_{ij} = \frac{1}{1 + e^{\gamma \cdot D}}, \tag{10}$$

where

$$D = d_{ij} - d_s * (1 + S) \tag{11}$$

Here, S is a safety factor introduced to ensure respecting the defined safety distance d_s (to account for prediction errors). The evolution of A_{ij} versus D is illustrated in Figure 3. Factor γ is a tuning parameter that determines the transition between the values 1 and 0.

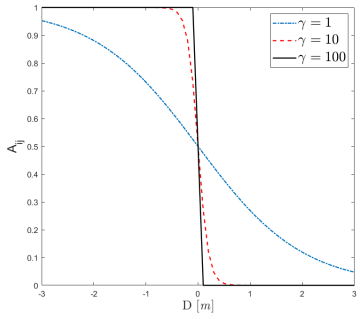

Fig. 3. Weight function A_{ij} for different values of the factor γ.

As the highest risk of collision may appear during the take-off and landing, the collision avoidance term outweighs the

trajectory tracking term in the cost function. On the other hand, minimizing the tracking error is a priority during the rest of the mission. Therefore, A_{ij} is a sigmoid function that helps avoid numerical issues due to the choice of a binary term (switch between 0 and 1 depending on the distance).

C. Collision avoidance through a flight corridor

As a safety mechanism to reject disturbances and model uncertainties, the flight corridor is introduced as a nonlinear constraint in the optimal control problem to ensure trajectory tracking within allowed limits. A flight corridor is represented as a tube with a set radius from the desired trajectory. Alone, it can ensure collision avoidance as each UAV stays inside its own corridor, which is constructed such that the corridor of the UAV does not intersect with the planned trajectory of the other UAVs in the system.

In this case, the control input is chosen to minimize the classical NMPC as in (7) while respecting additional constraints to remain in the defined boxed corridor, similarly as in [13]:

$$| p_\bullet - p_\bullet^{ref} | \leq \beta, \tag{12}$$

where $p_\bullet$ are the actual positions p_x, p_y or p_z, and $p_\bullet^{ref}$ position references along 3 axes. In order to ensure collision avoidance, the choice of the corridor width in 3 axes, β, depends on the size of UAV, as well as the *a priori* planned paths of all the UAVs.

V. Simulation results and discussion

A. Mapping mission trajectory tracking

In order to assess the robustness of the previously presented control strategies for trajectory tracking with collision avoidance in a mapping mission (Figure 1), the analysis of the Monte Carlo simulations will be presented here. Random values of constant external disturbances $[w_x, w_y, w_z]$, and uncertainty of the model parameter of the thruster efficiency α are considered for all the test cases. Simulation parameters are given in Table II.

TABLE II
Parameter values

g	$9.81m/s^2$	T_e	$0.1s$
A_x, A_y, Az	$(0.1, 0.1, 0.2)s^{-1}$	N_p	10
K_ϕ, K_θ	1	T_f	$10s$
τ_ϕ, τ_θ	$(0.7, 0.5)s$	d_s	$0.55m$
$Q_1 = Q_2$	$diag(10^2, 10, 10^2, 10, 10^3, 10)$	S	10%
$R_1 = R_2$	$diag(1, 1, 1)$	β	$0.3m$
G_{12}	100		

Parameters d_s and β are chosen according to the size of the UAV and the mission path plan. Here, simulations are performed for DJI Mavic 3, with the dimensions 347,5 x 283 x 107,7 mm (with propellers).

Monte Carlo simulations were conducted for 50 test cases with randomly added bounded external disturbances and uncertainties on thruster efficiency, denoted w_1, α_1 and w_2, α_2 for UAV1 and UAV2, respectively. All the optimization problems were solved by the same algorithm (*fmincon* of Matlab).

It is important to verify whether the minimum safety distance d_s is respected along the trajectories in all the test cases. In order to challenge collision avoidance, the imposed safety distance $d_s = 0.55m$ is superior to the distance between the reference paths of the two UAVs. Figure 4 shows the minimum reached distance between the UAVs along the mission. Nonlinear constraint and penalty cost strategies successfully avoid entering the imposed collision risk zone, whereas the flight corridor strategy violates the safety distance in certain test cases because the planned reference paths are *a priori* configured in overly close proximity to each other.

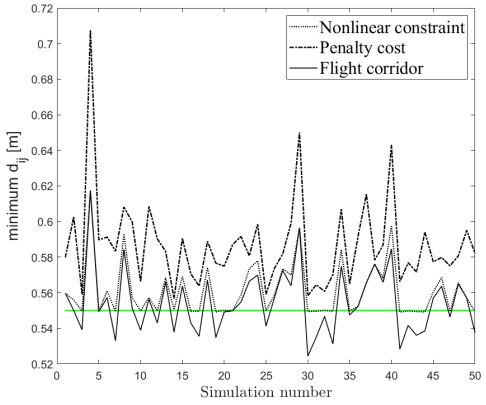

Fig. 4. Minimum distance between the UAVs along the trajectory. $d_s = 0.55m$ (in green).

Table III shows the root mean square error (RMSE) of the tracking error along the trajectory for the UAV that handles collision avoidance. The best results in terms of the tracking error, both the error value and the uniformity of the results, are exhibited for the flight corridor. As the flight corridor restricts the deviations from the reference path, it ensures that the UAV remains within the imposed limits, even in the presence of high model uncertainty and external disturbances. Collision avoidance in the cost function criterion shows the highest average tracking error, as it outweighs the trajectory tracking term at take-off and landing, when the UAVs are in high-risk collision zone.

TABLE III
RMSE for each strategy based on Monte Carlo simulation results

RMSE [m]	min	max	mean
Nonlinear constraint	0.08	0.85	0.15
Penalty cost	0.30	0.97	0.51
Flight corridor	0.08	0.23	0.13

When selecting the adequate control strategy, computational complexity needs to be considered. CPU time needed to solve the optimal control problem is an indicator of the complexity. Based on the results shown in Table IV, collision avoidance as the nonlinear constraint indicates the highest computational complexity among all strategies. It should be noted that resulting CPU time is given only as an indication for comparison, and as such is not compatible with real-time application.

TABLE IV
Average CPU time for each strategy based on Monte Carlo simulation results

Average CPU time [s]	min	max	mean
Nonlinear constraint	0.67	1.58	0.89
Penalty cost	0.54	1.06	0.78
Flight corridor	0.29	0.65	0.46

When comparing the two indicators, root mean square tracking error and computational complexity, flight corridor seems to be the highest-performing collision avoidance strategy for the presented path configuration.

In order to examine the simulation results in more detail, the worst case (here case test 4, see Figure 4) in terms of

RMSE is given in Figure 5. Indeed, from the resulting trajectory for UAV1, the lower-passing priority UAV handling collision avoidance, it is visible that only the flight corridor succeeds in tracking the reference path without major deviations. When looking into the disturbances and uncertainties values for test case 4, it can be assumed that the cause for high RMSE lies mainly in the overestimated thruster efficiency, which is much lower than predicted. As this parameter uncertainty highly affects the UAV position in the z-axis, the largest tracking error is in that direction. Only the flight corridor is robust to higher uncertainties for thruster efficiency α by maintaining the tighter constraints on the resulting trajectory. Flight corridor, therefore, appears to be robust to both external disturbances and model uncertainties.

When considering a test case in Figure 6, that results in lower values of RMSE for the UAV1, it is visible in Figure 6 that both nonlinear collision avoidance constraint and flight corridor succeed in tracking the planned path with only a small error. On the other hand, collision avoidance in the cost function deviates from the planned path when landing, as the risk of collision arises due to the close proximity of the UAVs. Nonetheless, most of the mission is tracked successfully for that strategy as well. From this test case, it is clear that underestimating the real capacity of the thruster (here: $\alpha_1 = 1.16$) does not impose difficulties for robust trajectory tracking.

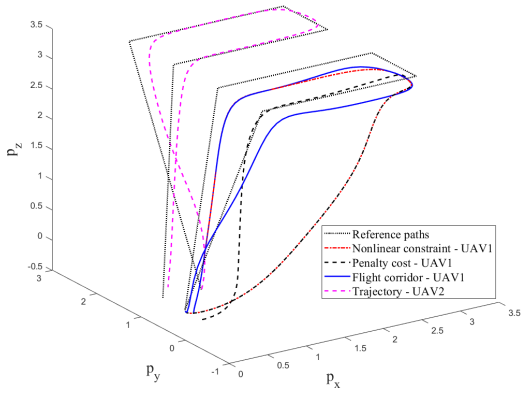

Fig. 5. Resulting trajectories for a test case (worst case scenario) with the external disturbances and model uncertainties.
$w_1 = [0.27, -0.63, 0.09] \quad m/s^2, \quad w_2 = [0.30, -0.61, 0.07] \quad m/s^2.$
$\alpha_1 = 0.71, \quad \alpha_2 = 1.14.$

B. Intersecting paths

The above-presented results illustrate a mapping mission where the planned paths of two UAVs do not intersect. However, due to unpredicted events, such as insufficient battery left to finish the mission, the trajectories need to be replanned. As the modified trajectories risk intersecting in case of an emergency return to base, collision avoidance becomes crucial for mission safety. An example of the intersecting reference paths is illustrated in Figure 7. The resulting trajectories and success in avoiding the collision depend on the implemented NMPC strategy. Figure 8 shows the resulting distance between the UAVs along their intersecting paths in the nominal case, without model uncertainties and external disturbances. It is clear that imposing the flight corridor is not sufficient to avoid the collision, as it only ensures that the UAV remains within the imposed limits, and does not address the collision risk itself. Implementing a nonlinear constraint ensures that defined safety

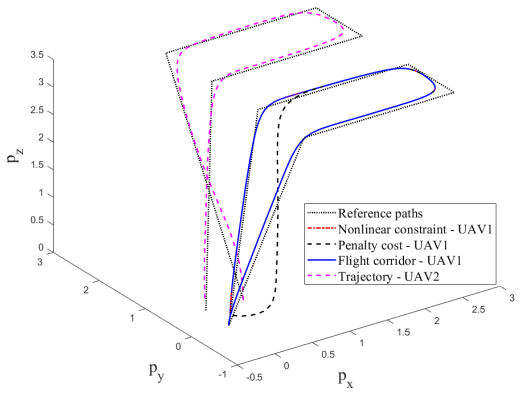

Fig. 6. Resulting trajectories for a test case (good performance scenario) with the external disturbances and model uncertainties.
$w_1 = [-0.18, 0.12, 0.02] \quad m/s^2, \quad w_2 = [-0.27, 0.04, 0.06] \quad m/s^2.$
$\alpha_1 = 1.16, \quad \alpha_2 = 1.12.$

distance is respected along the trajectory. In Figures 8 and 9, the trajectory with imposed nonlinear strategy overlaps with the one with the flight corridor, until it enters the zone of risk. When the reference paths present a risk of collision, NMPC with a nonlinear constraint keeps the safety distance, after which it continues to track the reference position with high precision. Implementation of collision avoidance as a penalty cost results in a higher level of deviation from the reference path for a longer time. Minimizing the tracking error is a priority at the beginning, where the distance between the UAVs is sufficient. However, as soon as the risk of collision arises, the UAV starts to avoid the collision by flying further apart from both the other UAV and its own reference path.

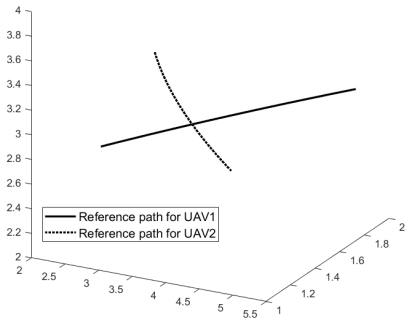

Fig. 7. Intersecting replanned reference paths.

In the presented case, the best compromise between minimal tracking error and collision avoidance guarantee is shown by implementing the NMPC with a nonlinear constraint to avoid collision. The resulting trajectories of both UAVs for the studied case are illustrated in Figure 10. The trajectory of the lower-priority UAV deviates in order to avoid the collision as soon as it enters the collision risk zone. The other UAV prioritizes minimal tracking error along the whole trajectory, and, therefore, has no trajectory alternations.

VI. Conclusion

In this paper, we compared three NMPC strategies for collision avoidance in multi-UAV missions with prioritized planning:

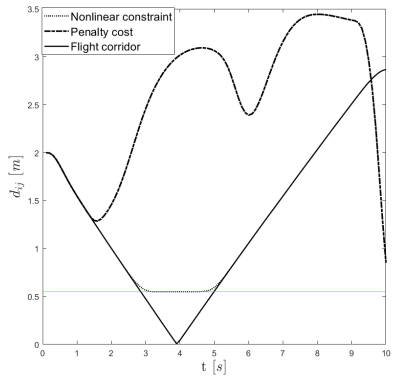

Fig. 8. Collision avoidance strategy comparison for intersecting reference paths, $d_s = 0.55m$ (in green).

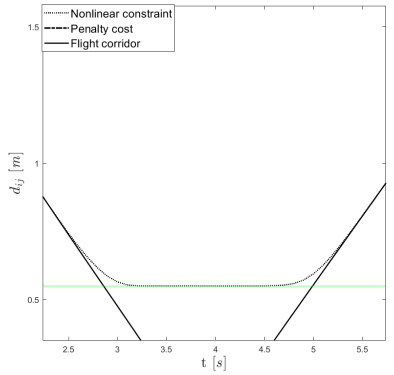

Fig. 9. Collision avoidance strategy comparison for intersecting reference paths (zoomed), $d_s = 0.55m$ (in green).

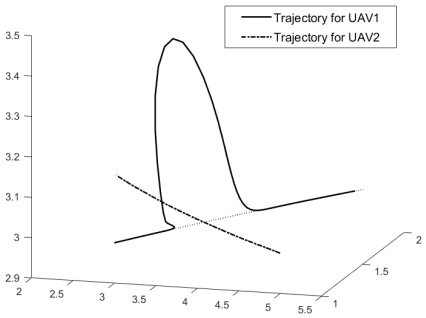

Fig. 10. Resulting trajectories for intersecting paths. UAV1 handles collision avoidance by implementing the NMPC with nonlinear constraint.

collision avoidance as a nonlinear constraint, collision avoidance as a penalty cost and safety flight corridor.

When comparing the Monte Carlo simulation results for the considered mapping mission case with the planned paths for the UAVs that do not intersect, the flight corridor appears to be the best-performing strategy in terms of robustness to external disturbances and model uncertainties. Compared to the other two strategies, the flight corridor ensures low tracking error in all the tested scenarios. As it prevents the UAV from leaving the safety distance margin, it also ensures that no collision will appear if the parameters are chosen correctly, and there are no collisions in the planned path for the UAVs included in the mission. Computational time for solving the control problem is also inferior in comparison to the other two methods.

However, in case of online replanning the mission that results in the UAV crossing paths, imposing the flight corridor constraint is not sufficient. In that case, additional safety mechanisms, such as imposing a nonlinear constraint, need to be implemented to guarantee collision avoidance.

Future work will include more UAVs in the mapping mission, where the passing priority allocation and path replanning will be performed online. Also, NMPC with flight corridor applied to a mapping mission is planned to be experimentally validated. Therefore, an adequate solver needs to ensure real-time application of the NMPC [3].

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